RBFNN Node Importance Evaluation in Aviation Network Based on UKF Learning Algorithm

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Abstract: To evaluate the nodes in aviation network for key nodes identification, a RBFNN (RBFNN) node evaluation method using UKF learning algorithm is proposed for aviation network. RBFNN based on UKF learning algorithm (UKF-RBFNN) is firstly studied for evaluation modeling, and then UKF-RBFNN model, with the simple indices of network node as the inputs, and the comprehensive importance of node by complex indices as the outputs, is established. Simulation shows that the proposed method is effective and feasible for Node importance evaluation in aviation network.

1. RBFNN

RBF Neural Network (RBFNN) [1] is a feed-forward neural network with excellent performance. RBF network can approximate any nonlinear function through arbitrary precision, and has the ability of global approximation, solving the problem of local optimum BP neural network radically, and its topology structure is compact, its structure parameters can realize the separation learning with fast convergence speed [2]. The advantages of RBFNN mainly include:

1) It has unique optimal approximation properties without local minimum.

2) RBFNN has strong mapping function for input and output, and it has been proved that, in feed-forward neural network, RBFNN is the best network completing the mapping function.

3) Relationship between connection weights and output of network is linear.

4) It has a good classification ability.

5) Learning process has a rapid convergence speed.

In fact, RBFNN generally has only one hidden layer with RBF activation function. For Fig.1 shows the structure of RBFNN, the expression of RBFNN is as follows:

$$z = \sum_{i=1}^{n} \omega_i f(\| x - C_i \| / \delta_i) \tag{1}$$

or if considering threshold value we have

$$z = \sum_{i=1}^{n} \omega_i f(\| x - C_i \| / \delta_i) + d \tag{2}$$

where ω_i is the connection weight of output layer, C_i is the center of radial basis function, $f(\cdot)$ is the RBF function, $x \in R^n$ is the input of neural network, δ_i is the sensitive domain of RBF, d is the threshold value of output layer, $\|\bullet\|$ is the distance operator, n is the number of hidden neurons.

Suppose that the training samples $S_m = \{X_i, Z_i\}$, $i = 1, 2, \cdots, m$, then the training process of

RBFNN is to hunt for $\Theta = \{C_i, \delta_i, \omega_i\}$ to acheive the minimization of following function

$$\min e_{RBF}(S_m, F_n(X,\Theta)) = \frac{1}{m}\sum_{i=1}^{m} | Z_i - F_n(X,\Theta) |^2 \tag{3}$$

$$F_n(X,\Theta) = \sum_{i=1}^{n} \omega_i f(\| x - C_i \| / \delta_i) \tag{4}$$

Because the output layer of RBFNN is the linear neurons, so as long as C_i and δ_i are determined, the parameters of output layer can be constructed by least square method. In RBFNN learning algorithm, the main task is to search the optimal vector $\Theta = \{c_i, \sigma_i, w_i\}$.

2. UKF algorithm

UKF is a novel Kalman filter for solving the nonlinear system based on Unscented Transformation (UT), which has attracted great attention. UKF approximates the random variable distribution by generating a discrete distribution comprising the minimum number of points that preserves the same first and second order moments, and has the faster convergence rate and higher precision without computing Jacobian matrix [3][4].

Suppose that a nonlinear discrete system is defined as follows:

$$x_k = f(x_{k-1}) + w_k \tag{5}$$

$$y_k = h(x_k, u_k) + v_k \tag{6}$$

where x_k is the unknown state of system. y_k is the measurement output of system. w_k is the process noise which is the white noise with zeros mean and covariance Q_k. v_k is the measurement noise which is the white noise with zeros mean and covariance R_k.

For the above-defined system, the steps of UKF is as follows:

1) Initialization

$$\hat{x}_0 = E\left[x_0\right] \tag{7}$$

$$P_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right] \tag{8}$$

2) Calculate the sigma-point x_{k-1} using the method as introduced in the reference [7]

$$x_{k-1} = \hat{x}_{k-1} + \sqrt{P_{k-1}} X_{sigma} \tag{9}$$

3) Time update

$$x_{k|k-1} = f(x_{k-1}) + w_k \tag{10}$$

$$\hat{x}_k^- = \sum_{i=1}^{n+1} \omega_i x_{i,k|k-1} \tag{11}$$

$$P_k^- = \sum_{i=0}^{n+1} \omega_i \left[x_{i,k|k-1} - \hat{x}_k^-\right]\left[x_{i,k|k-1} - \hat{x}_k^-\right]^T + Q_k \tag{12}$$

$$y_{k|k-1} = h(x_{k|k-1}, u_k) + v_k \tag{13}$$

$$\hat{y}_k^- = \sum_{i=0}^{n+1} \omega_i y_{i,k|k-1} \tag{14}$$

4) Measurement update

$$P_{k|k-1}^{yy} = \sum_{i=0}^{n+1} \omega_i \left[y_{i,k|k-1} - \hat{y}_k^- \right]\left[y_{i,k|k-1} - \hat{y}_k^- \right]^T + R_k \tag{15}$$

$$P_{k|k-1}^{xy} = \sum_{i=1}^{n+1} \omega_i \left[x_{i,k|k-1} - \hat{x}_k^- \right]\left[y_{i,k|k-1} - \hat{y}_k^- \right]^T \tag{16}$$

$$K_k = P_{k|k-1}^{xy} (P_{k|k-1}^{yy})^{-1} \tag{17}$$

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - \hat{y}_k^-) \tag{18}$$

$$P_k = P_k^- - K_k P_{k|k-1}^{yy} K_k^T \tag{19}$$

3. RBFNN Learning process of based on UKF algorithm

The state space model is a dynamic model in time domain in which the connotative time is regarded as the argument. Application of state space model in the analysis of time series are increasing rapidly. The state space model that is more commonly applicated is the canonical correlation method proposed by Akaike and further evolved by Mehra. The new method of state space model that can estimate the vector value proposed by Aoki et al can get the state space model with so-called internal balance, if only the corresponding element in the system matrix can be removed, any low order approximation model can be obtained without re-estimation, and as long as the original model is stable, low order approximation model obtained is also stable.

Learning of RBFNN is optimal estimation for the network parameters Θ (including c_i, σ_i, w_i) so as to search the optimal network parameters. Therefore, Θ is taken as the state variables of the network system, the output as the measurement equation of the network, the state space model of RBFNN can be expressed as

$$\Theta_{t+1} = \Theta_t + \eta_t \tag{20}$$

$$z_t = f(X_t, \Theta_t) + \mu_t \tag{21}$$

where X_t is the input of the network, z_t is the output of the network, $f(X_t, \Theta_t)$ is the nonlinear function parameterized. η_t is the process noise and in paper is taken as Gauss white noise with mean 0 and variance Q_t, η_t is the measurement noise and in paper is taken as Gauss white noise with mean 0 and variance R_t, noise.

Through UKF training RBFNN, we can use UKF algorithm to obtain the optimal parameter vector $\Theta = \{c_i, \sigma_i, w_i\}$. The training flow of RBFNN using UKF algorithm is shown in Fig. 1, where Mean Square Error (MSE) is taken as the error indicators of network training.

4. UKF-RBFNN evaluation process of node importance

In the papaer, Node importance evaluation process [5][6] using UKF-RBFNN is shown in Fig. 2. In node evaluation modeling for aviation network, we need to explain the following points:

Inputs of UKF-RBFNN: simple indices such as node degree value, point strength, and K-shell value.

Output of UKF-RBFNN: node comprehensive importance. Node comprehensive importance can be calculated by complex indices such as Closeness Centrality (*CC*), *B*etweenness Centrality (*BC*), Link Density (*LD*), and Network Efficiency (*NE*). the calculation formula Y_i=0.5789BC_i+ 0.2055NE_i +0.1592CC_i+ 0.0565LD_i.

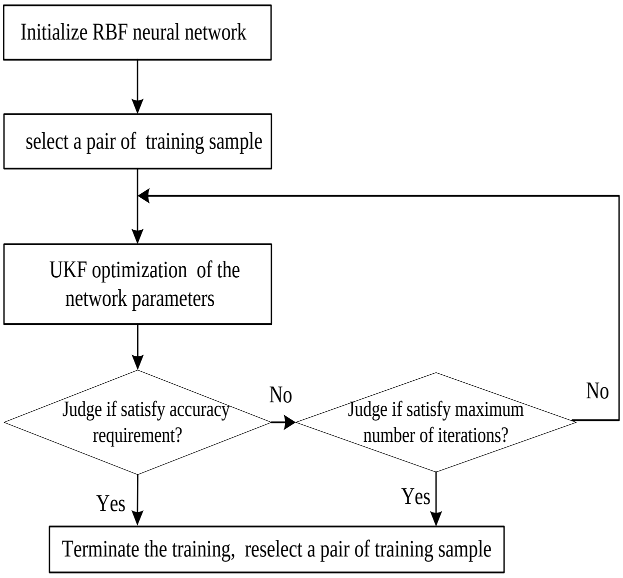

Fig.1 Flow of UKF-RBFNN

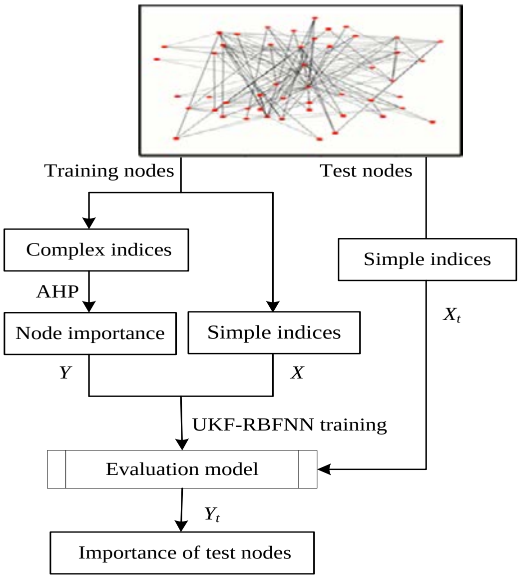

Fig. 2 Node importance evaluation process

5. Simulation

In simulation, U.S. aviation network can be selected. The experiment data [7] include 332 airport nodes, 2126 edges (direct flight routes) and the weights of the edges. 40 nodes in aviation network are taken as the training samples of UKF-RBFNN, the remaining nodes are evaluated and sorted after the test is terminated. Compare with the original Complexity Index Evaluation (CIE) importance sorting and ACI sorting, we give the sorting result obtained, as shown in Table 1. Among them, ACI refers to the comprehensive sorting of US airports by the International Airports Council.

Table 1 Sorting of US airport node importance

Sorting	Method		
	ACI	CIE	UKF-RBFNN
1	Hartsfield Atlan	Chicago O'hare	Chicago O'hare
2	Chicago O'hare	DFW	DFW
3	DFW	Hartsfield Atlan	Hartsfield Atlan
4	Stapleton	San Francisco	G.Bush
5	Los Angeles	G.Bush	San Francisco
6	Mc Carran	MSP	MSP
7	G.Bush	Charlotte/Douglas	Charlotte/Douglas
8	Charlotte/Douglas	JFK	JFK
9	P S H	Mc Carran	Mc Carran
10	Philadephia	Anchorage	Anchorage
11	DMW	Lambert-St Louis	Lambert-St Louis
12	MSP	Bethel	Stapleton
13	JFK	Stapleton	Bethel
14	Newark	P S H	DMW
15	San Francisco	Salt lake city	P S H
16	Salt lake city	DMW	Salt lake city

From the sorting comparison, it is not difficult to find that the top 16 airport nodes in the test results (simple index evaluation results) are only three different from ACI, indicating that the proposed method is more realistic and has certain accuracy. Comparing the test results with the evaluation results of complex indices, it is found that the results of the two methods are almost the same. Among the first few, only San Francisco and G. Bush have reversed the order, and the latter are slightly different, indicating the learning effect of UKF-RBFNN is very good, and it has the ability to accurately predict data.

In order to verify the generality of the algorithm, UKF-RBFNN is applied to Chinese aviation network. We take 199 Chinese cities with scheduled flights in 2016 as target nodes, crawl and collect webpage data, construct aviation network model, and identify key nodes of aviation network. The accuracy of the test results is shown in Fig. 3. It is not difficult to see that the test results are generally consistent with the actual values in trend.

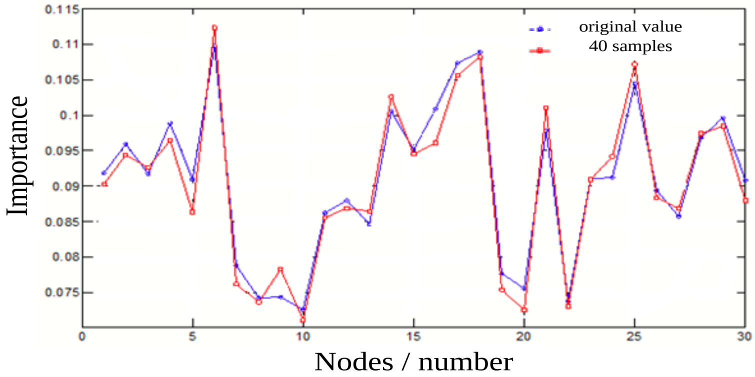

Fig. 3 Comparison of test result and original value

6. Conclusions

To evaluate the nodes in aviation network, the simple indices such as node degree value, point strength, and K-shell value are select as the inputs of UKF-RBFNN, the comprehensive importance of nodes obtained by Closeness Centrality (*CC*), *B*etweenness Centrality (*BC*), Link Density (*LD*) and Network Efficiency (*NE*) are taken as the outputs. Training UKF-RBFNN can get the mapping relationship between simple indices and comprehensive importance. The simulations on U.S. aviation network and Chinese aviation network show that the proposed method is effective and feasible in node importance evaluation.

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